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The Effect of External and Internal Noise on the Performance of Chaotic Neural Networks

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ABSTRACT

Biological evidence suggests that information encoding in the form of oscillatory patterns is advantageous compared to convergent, fixed-point type memories. Freeman's KIII model is an example of operational chaotic memory neural networks. Noise plays a constructive role in the model by maintaining and stabilizing aperiodic orbits. Gaussian noise components are injected to the model at different locations: at the input channels and also at a centrally located internal node. Depending on the noise intensity and bias, resonance effects have been identified in the KIII model. The observed noise effects have some similarity with stochastic resonance, but there are very essential differences. The interaction of noise with the oscillatory signal has a resonance character in the KIII model. The oscillatory signal in KIII, however, is not coming from the external world, but it is the result of the interaction of the various internal components. Therefore, the signal has an intimate interference with the noise. These effects are illustrated in pattern recognition problems.

Keywords: Chaotic Neural Memory, Noise, Freeman Network, Pattern Recognition.

1. INTRODUCTION TO CONVERGENT AND OSCILLATORY NEURAL NETWORKS

An overwhelming part of neural networks today uses fixed point convergence for information encoding. The reason of the wide proliferation of convergent NNs is their relative simplicity, the existence of firm mathematical foundations established during a latent period in the 60 s and 70 s, and the explosive development of this field in the 80 s. The past decade showed a wide range of impressive applications of NNs together with other connectionist, soft computing technologies in the field of, e.g., pattern recognition, system identification, and adaptive control, see Schwartz (1990).

There is a growing number of neural network models that use nonlinear dynamics for information processing. Often these models use limit cycle oscillations for encoding and retrieving data Fukai & Shiino (1992), Wang (1998). Using bifurcation sequences of an attractor in a high-dimensional space can serve to that purpose. In equilibrium NNs, the stored memory patterns correspond to local minima of the static landscape of the network energy function. The shape of this energy function can be very complex and it may contain a lot of spurious local minima preventing the correct retrieval of certain patterns. Limit cycle-based NNs do not suffer from this problem as they encode the patterns not in a single minimum, but in a finite sequence of jumps.

Another advantage of limit cycle encoding is memory efficacy. The number of patterns memorized by equilibrium NNs cannot exceed the number of fixed points of the dynamics, which, in turn, are strongly limited as the function of the number of processing elements. Bifurcative NN encoding schemes have higher memory capacity by realizing an encoding as a combination of jumps among the fixed points of the dynamics. As a whole, however, the memory is still linked to the fixed points of the dynamics in both equilibrium and bifurcative schemes.

In typical equilibrium type encoding systems, the noise and the overlap of the pattern classes is undesirable. In non-equilibrium NNs, the noise can play a completely different, constructive role. Examples are the noise-mediated signal enhancement in stochastic resonance (SR) Gammiatoni et al. (1998) and the stabilization of aperiodic attractors by sensory and central noise in the Freeman KIII sets; Freeman (1994).

excitatory (E) or inhibitory (I) K0 sets, KI_E or KI_I sets are formed, respectively. The interaction of KI_E and KI_I sets constitutes the KII set. Finally, coupling several KII sets with excitatory, inhibitory feed-forward and feedback loops, one arrives at the KIII set.

The KIII model is an example of layered networks with nonlinear units having the following types of coupling: (i) feed-forward connections between layers, (ii) lateral excitation or inhibition across certain layers, (iii) feedback connections between layers. Decade-long studies indicate that this class of networks can exhibit a wide range of dynamic behaviors, i.e., fixed point and limit cycle attractors, quasi-periodic oscillations and chaos. KIII models can grasp the essence of the observed dynamic behavior in certain biological neural networks, including that of the olfactory system, Freeman (1992). In the KIII model of the olfaction the layers correspond to: receptors (R), periglomerular cells (P1 and P2), olfactory bulb (OB), anterior olfactory nucleus (AON), prepyriform cortex (PC) and deep pyramidal cells (C). There is a general feed-forward structure from R to P1 and OB, and from OB to AON and PC via the lateral olfactory tract (LOT). Lateral connections are incorporated at the OB at two levels, while feedback is directed from PC to AON, from C to OB, and from AON to OB and P1 via the medial olfactory tract (MOT). The OB, the AON and PC are all examples of interconnected KII sets.

The operation of the memory can be described as follows. In the absence of stimuli the system is in a high dimensional state of spatially coherent basal activity. The basal state is described by an aperiodic (chaotic) global attractor. In response to external stimulus, the system can be kicked-off from the basal state into a local memory wing. This wing is usually of much smaller dimension than the basal state. It shows coherent and spatially patterned amplitude-modulated (AM) fluctuations. After the residence of the system in this localized wing, it returns to the basal state. This is a temporal burst process having a duration of about 100 ms. A memory pattern is defined therefore as a spatio-temporal process represented by the sequence of spatial AM patterns during the burst.

The KIII model has been used to actually implement the above memory process. Using advanced optimization techniques, the system can be trained to learn a collection of given patterns (Chang and Freeman, 1996). There is a problem, however, in the utilization of the KIII model as a powerful dynamical memory device. It is the fragmentation of the global aperiodic (chaotic) attractor into quasi-periodic local attractors, following input-induced state transitions. The optimized system is extremely sensitive to small changes in system parameters due to attractor crowding (Chang et al., 1998) which practically prevented effective generalization. This problem has been the impediment of further progress in this field for several years.

Attractor crowding is an unavoidable manifestation of the complexity of the high-dimensional chaotic KIII system. Highly evolved, fractured attractor boundaries are found, which produce a mixture of various attractors in a small neighborhood of a typical point of the state space. As the external conditions vary, the low-dimensional subspace into which the system collapses also changes. The complicated landscape indicates that fine-tuning the system parameters to a narrow section of the given attractor could be a daunting and practically unfeasible task. As an important development in the theory and implementation of dynamical memories, it has been shown that attractor fragmentation can be effectively utilized in building robust memories Kozma and Freeman (1999, 2000). Accordingly, we acknowledge the co-existence of a range of attractors in any actual realization of the system and build robust KIII dynamics in this way.

The main idea is illustrated on the example of the relatively simple KII subsets. Various KII set can be identified in the olfactory system, as OB, AON, and PC. The impulse responses of these KII sets are decayed oscillations. There are, however, important differences in the asymptotic behaviors. Physiological evidence shows unbiased fixed point for the OB, and inhibitory and excitatory bias for PC and AON, respectively; see Freeman (1992). Parameter studies show that there are significant overlaps among the attractors, depending on the initial conditions. This behavior resembles the partially ordered phase-type attractors (glassy or intermittent) in globally coupled lattices, Kaneko (1990). Details of the dynamical behavior of KII sets are given in Kozma and Freeman (2000). In this paper, we concentrate on the highest level dynamics of the KIII model.

4. PATTERN RECOGNITION USING SPACE-TIME ENCODING

There are several requirements toward a biologically plausible model of chaotic memories. Remaining with the example of the olfaction, these conditions can be formulated as follows, Freeman et al. (1997):

- broad band aperiodic fluctuations in the basal state of the olfactory bulb with 1/f- type power spectral densities,
- spatially coherent behavior in the olfactory bulb,
- temporal fluctuations at various levels should have close to normal distribution in the basal state,
- the magnitudes of the wave density signals of the periglomerular (PG) cells should concentrate on the right of the maximum gradient of the asymmetric wave-to-pulse transfer function,
- the magnitudes of the wave densities of the signals in the olfactory bulb should concentrate on the left of the maximum derivative of the transfer function,
- phase transition should occur swiftly, within about 10 ms after the onset/termination of the stimuli.

The KIII model satisfies these conditions and it can be considered as a biologically realistic model of measured EEG signals.

In the KIII model, several learning tools are used. One is the Hebbian learning of stimulus patterns, the other is habituation of background activity. Habituation can be modeled as weight decay in the form of forgetting, as it is described in the previous sections. A third mechanism involves nonlinear adaptive control techniques aiming at the stabilization of the trajectories. All these learning methods exist in a subtle balance and their relative importance changes at various stages. As a read-out procedure from the KIII model, AM patterns are calculated for the 8x8lattice on the Mitral level..

The KIII model is used for the classification of the experimentally observed RMS data. Experiments have been conducted with rabbits which were chronically implanted with square arrays of 64 (8x8) electrodes. The rabbits have been trained to recognize two types of visual stimuli. The measured data in the form of 64-dimensional patterns have been used as input patterns to the KIII model. Readout is conducted at the mitral level (3^{rd} layer) of KIII in the form of gamma-band (40Hz to 80 Hz) oscillation intensity.

Examples of the EEG rms patterns are shown in Fig. 1. One can see clear differences in the rms patterns corresponding to the different stimuli. At different time steps, the differences can become less obvious or even confusing, as it is seem in Fig. 1. The change of the spatial AM magnitude pattern during the input induced phase transition is clearly visible. However, there is no 'fixed' pattern of rms for identification. Rather we have to rely of the sequence of somewhat blurred patterns with intermittent fluctuations in our classification task.

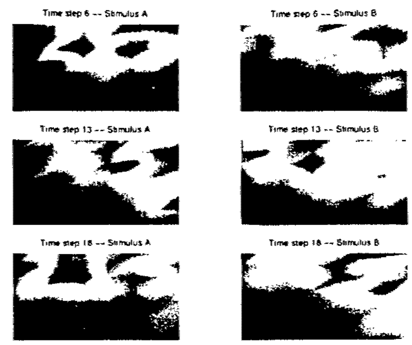

Figure 1 Spatio-temporal sequence of AM patterns; post-stimulus signal analysis of rabbit experiments with two visual stimuli: A and B. The time step of the image processing is 64 ms; sampling time is 1 ms.

We used 5 patterns from both classes for the training in 10 sequential steps. Consecutively, the trained model has been used for classifying 30 untrained patterns (15 from each class). In the classification we have evaluated the Euclidean distance between a given pattern and the previously determined centers of the two classes. We evaluated these distances for the RMS patterns calculated on the OB level in the model and compared it with the classification based on the distances obtained for the original input data sets.

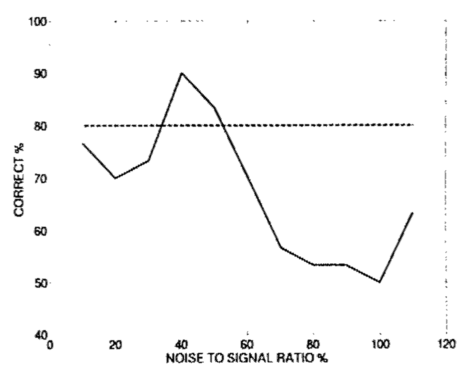

Figure 2: Classification performance of KIII (solid line); the classification performance of the pure statistical clustering method is shown by dash. Note the significant improvement of the performance of the model at moderate additive noise levels.

The results are summarized in Figure 2, where the correct classification rate of the KIII model is shown in solid line. The classification rate based on the

original input EEG rms data (without noise) is given in dashed line. It is seen that, by applying moderate additive noise levels, we could achieve an improved classification performance by KIII compared to the pure clustering method.

5. ROLE OF NOISE IN THE MEMORIES

In this section, the relation between the aperiodic behavior of the KIII and typical low-dimensional deterministic chaos is discussed. Also, we explain the novel features of parametric noise effect in the KIII model in the context of stochastic resonance (SR). SR is another interesting application of information processing in noisy chaotic systems. SR has become a well-established research field during the past two decades and it is widely applied in various disciplines, from laser physics, semiconductor devices, through neurophysiology. SR effect can arise in a bi- or multi-stable system with an energy threshold between the states. External or internal noise can initiate a transition between the states. This effect has a resonance character and it can be used to enhance a weak (periodic) input signal, thus producing a high signal-to-noise ratio. For an overview of this field, see Gammaitoni et al. (1998), Assumian & Moss (1998). Examples of successful implementation in neural systems are Moss & Pei (1995), Bulsara et al. (1996), Mitaim & Kosko (1998), among others.

It is very likely that brains use resonance effects in a more subtle way than it is suggested by the original SR theory. This issue will be elaborated further in connection with the properties of the Freeman KIII nets. Noise has a special role in the KIII model. There are Gaussian noise components injected at different locations: at the input channels and also centrally at the AON. The input noise is spatially independent and rectified while the central noise in centrifugal and uniform in space with possible bias. Depending on the noise intensity and bias, resonance effects have been identified in the KIII model.

Brain chaos has been analyzed experimentally and theoretically and it is called stochastic chaos by Freeman (2000). These noise effect have some similarity with stochastic resonance but they have very crucial differences as well (Kozma & Freeman, 1999). A comparison of SR and KIII resonance is given in Table I. SR has 3 main components: a bi- or multi-stable energy function, weak (periodic) input signal and noise. The addition of noise can enhance the signal-to-noise ratio which is of great practical importance for signal processing applications. The interaction of noise with the oscillatory signal has a resonance character in the KIII model as well. The oscillatory signal in the KIII model, however, is not coming from the external world, but it is the result of the interaction of the various internal KII components. Therefore, the signal may have an intimate interference with the noise in a KIII system, as compared with the pure input/output relationship in the case of SR. Another difference is that the energy function is fixed in SR while the complex energy function can be adapted in the KIII model.

6. CONCLUDING REMARKS

The KIII model produces biologically plausible results that are used for the interpretation of EEG measurements conducted in mammalian olfactory systems. Intensive future studies are required to discover the complexity of the dynamics of rules inferred from various neural networks and to utilize them in understanding intelligence in computational and biological systems.

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Table I Stochastic Resonance versus Parametric Noise in KIII

Stochastic Resonance (SR)	Parametric effect of noise in KIII
Fixed bi- (multi-) stable nonlinear system	Continuously changing multi-stable nonlinear system
Weak (periodic) signal transmitted	The fluctuating carrier signal originates from inside
External and internal noise magnifies the input signal by de-stabilizing chaos	Input and central noise stabilizes the system and amplifies the chaotic signals
Maximum signal-to-noise ratio at a well-defined noise level (resonance)	Maximum amplification at some intermediate noise level
Components are chaotic	Components are not chaotic and chaos is the collective feature of KIII